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Abstract

This paper conducts a *real-time*, out-of-sample analysis of the forecasting power of various aggregate financial intermediaries' balance sheets to a wide range of economic activity measures in the United States. I find evidence that the balance sheets of leveraged financial institutions do have out-of-sample predictive power for future economic activity, and this predictability arises mainly through the housing sector. Nevertheless, I show that these variables have very little predictive power during periods of economic expansions and that predictability arises mainly during the financial crisis period.

JEL classification: C53
Bank classification: Econometric and statistical methods

Résumé

Dans cette étude, l'auteur effectue une analyse en temps réel du pouvoir prédictif hors échantillon des données de bilan agrégées de divers intermédiaires financiers relativement à un large éventail de mesures de l'activité économique américaine. Il constate que les bilans des institutions financières à effet de levier permettent de prédire hors échantillon l'évolution future de l'activité économique, et que ce pouvoir se manifeste surtout par le canal du secteur du logement. Néanmoins, il montre que ces variables ont un pouvoir prédictif très faible en période d'expansion économique et que celui-ci apparaît principalement lors de crises financières.

Classification JEL : C53
Classification de la Banque : Méthodes économétriques et statistiques

1 Introduction

The extent of the recent turmoil in financial markets and its long-lasting spillover effects to the real economy has renewed interest in studies of the interaction between credit conditions and the macroeconomy. More meaningfully, it has called attention to the role played by financial intermediaries in the fluctuations of risk premia and economic activity.

This paper conducts a careful examination of the predictive power of different financial intermediaries' balance sheets to future changes in a wide set of economic activity measures in the United States. Unlike previous research, I conduct all my forecasting tests in an out-of-sample, *real-time* setting. I report evidence that the balance sheets of some financial intermediaries, namely security broker-dealers, and, to a lesser extent, shadow banks, have out-of-sample power in *real-time* for future economic activity. Nevertheless, I also find that the informational content of the balance sheets are quite unstable, accruing more significantly in recessionary periods, and/or times of financial stress. I then show, using data-rich forecasting methods, that the information contained in these balance sheets is roughly equal to that of traditional macrofinancial series in normal economic environments.[1] On the data front, I contribute to the real-time forecasting literature by constructing a quarterly real-time data set of aggregate financial intermediaries' balance sheets as released quarterly by the Flow of Funds of the Federal Reserve Board.

My results also point to the relevant channels through which fluctuations in financial intermediaries' balance sheets forecast economic growth. I find that the predictive power of these balance sheets for future GDP arises mainly through the housing sector. Fluctuations in broker-dealers' leverage and equity are strong predictors of expected real housing investment growth. This predictability is to a large extent orthogonal to the information contained in traditional macro and financial indicators.

Several papers have recently called attention to the importance of financial intermediaries' balance sheets for the economy. On the theoretical front, a large number of recent papers show how fluctuations in balance sheets of financial intermediaries impact economic activity and amplify economic shocks. Meh and Moran (2010), Christensen et al. (2011) and Sandri and

[1] I define normal economic environments as periods absent of recessions and financial crisis.

Valencia (2013) develop dynamic stochastic general-equilibrium (DSGE) models to study how financial intermediaries' balance sheets may amplify shocks to the economy, as well as become the source of economic activity fluctuations themselves, following significant disturbances to their net worth. These studies generally show that shocks to financial intermediaries' balance sheets have a much more disruptive effect on economic activity than shocks to households' or non-financial firms' balance sheets. This is mainly due to the higher leverage of financial intermediaries, which hinders their ability to buffer shocks to their net worth. Thus, an exogenous shock to financial intermediaries' net worth leads to a high reduction in their risk-bearing capacity, resulting in a significant cut in financial intermediation, and hence a fall in economic activity. By this same mechanism, one would expect that shocks to the highly leveraged financial intermediaries, such as broker-dealers, have a stronger potential to impact economic activity than shocks to the commercial banks' balance sheets.[2]

On the empirical side, Adrian and Shin (2010a) is one of the first studies to show that fluctuations in the balance sheets of financial institutions, especially broker-dealers, contain in-sample forecasting power for future GDP growth. Additionally, Adrian et al. (2010) argue that the balance sheets of broker-dealers and shadow banks have information for expected returns of various bond and equity markets in the United States.[3] This result holds in- and out-of-sample, as well as before the financial crisis. Nonetheless, these authors do not study the out-of-sample predictability of economic activity by means of these financial intermediaries' balance sheets. Kollmann and Zeugner (2012), on the other hand, show that the leverage of various sectors of the economy (financial, non-financial firms, and households) has both in-sample and out-of-sample forecasting power for economic activity. I add to their results by considering a real-time setting with additional financial intermediaries, more measures of economic activity, and by conducting a more systematic evaluation of the time-varying out-of-sample forecasting performance of the different models.

[2] For a comparison of the balance-sheet dynamics of commercial banks and broker-dealers, see Adrian and Shin (2010b) and Nuño and Thomas (2013).

[3] Additionally, Adrian et al. (2009) argue that fluctuations in the aggregate balance sheets of broker-dealers forecast exchange rate returns for a large set of countries at weekly, monthly and quarterly horizons, both in- and out-of-sample. Etula (2013) shows that broker-dealers' asset growth forecasts a wide range of commodity prices at quarterly horizons, both in- and out-of-sample.

The paper is organized as follows. Section 2 discusses the data. Section 3 provides an initial exploration of the forecasting power of balance sheets of financial intermediaries in a simple set-up. The next section explores how the forecasting power of financial intermediaries' balance sheets compares to traditional macroeconomic and financial predictors, and examines its time stability. Section 4 concludes.

2 Data

I use quarterly data of financial intermediaries' balance sheets, and macroeconomic and financial indicators from 1985Q1 to 2010Q4, to study the predictability of a diverse group of economic activity variables, namely: gross domestic product, industrial production, non-farm payroll, real private investment, real housing investment, and durable consumption. In this section, I detail how I constructed my financial intermediaries' balance sheets, as well as macrofinancial data set.

In assessing the marginal predictive content of financial variables for real activity using real-time data, an important issue is that the latter are constantly being revised. I follow Faust and Wright (2009) and use the data as recorded two quarters after the quarter to which the data refer as the realized value. For the national income and product accounts data, this corresponds to the data as recorded in the second revision.

2.1 Financial intermediaries' balance-sheet data

I investigate the predictive power of aggregate balance-sheet fluctuations of the following financial intermediaries: (i) *commercial banks* (CB), comprising commercial banks, credit unions and savings institutions; (ii) *securities broker-dealers* (BD); (iii) *shadow banks* (SB), comprising issuers of asset-backed securities, finance corporations and funding corporations; and (iv) *agency- and government-sponsored enterprise (GSE)-backed mortgage pools*.[4] Table

[4](i) Commercial banks are financial institutions that raise funds through demand and time deposits as well as from other sources, such as federal funds purchases and security repurchase agreements, funds from parent companies, and borrowing from other lending institutions, and use the funds to make loans, primarily to businesses and individuals, and to invest in securities. (ii) Broker-dealers are financial institutions that buy and sell securities for a fee, hold an inventory of securities for resale, or do both. (iii) Issuers of asset-backed securities (ABS) are

1 details the composition of all balance-sheet variables. For each financial intermediary, I collect data on total financial assets (A) and liabilities. Equity (E) is then calculated as assets minus liabilities (A-L). Leverage is defined as assets over equity (L=A/E).[5]

Contrary to most financial variables, which are not usually revised, but akin to standard macroeconomic data, the Flow of Funds data are subject to data revisions. Hence, in order to analyze the performance of the balance-sheet variables in a real-time setting, as the data were available to the forecaster at each period of time, I recovered vintage data available at the Federal Reserve Board website back to June 1999, the first available real-time vintage available. That date, then, is the starting period of my out-of-sample exercise. There is a trade-off in forecasting exercises on how to split the sample between the in-sample period for initial parameter estimation, and the out-of-sample evaluation period.[6] My choice of the starting period for the out-of-sample forecasts is determined by data availability. The models are estimated with data starting in March 1985. It was during this period, as shown by Adrian and Shin (2008, 2010a), which coincides with the "Great Moderation," that the market-based financial system became more prominent in the provision of credit in the economy.

Figure 1 plots the annual growth rate rate of all financial intermediaries' balance sheets, as recorded in the 2010Q4 vintage. Table 2 reports summary statistics. Broker-dealers', shadow banks' and mortgage pools' asset growth rates are, on average, significantly higher and more volatile than the ones for commercial banks. For example, whereas the average annual growth rate of Commercial Banks assets is 6.5% with a 3.5% standard deviation, that for broker-dealers is 14.9% with a standard deviation of approximately 21%.

special purpose vehicles (SPVs) that hold pools of assets (usually loans) in trust and use them as collateral for issuance of ABS. (iv) Agency- and GSE-backed mortgage pools are a group of mortgages used as collateral for a mortgage-backed security. For a full description of these financial intermediaries, see the Financial Accounts Guide at http://www.federalreserve.gov/apps/fof/.

[5]All variables are available at the Federal Reserve Bank Flow of Funds data. See http://www.federalreserve.gov/releases/z1/default.htm.

[6]Rossi and Inoue (2012) propose a methodology for evaluating out-of-sample forecasting performance that is robust to window size.

2.2 Macroeconomic and financial series

In order to compare the predictability provided by the aggregate financial intermediaries' balance-sheet variables to more traditional predictors, I construct a panel of commonly used macroeconomic and financial predictors of economic activity. Since I estimate the models with only real-time data, the panel is composed of significantly more financial than macroeconomic series: the number of potential financial predictors (which are not revised) is higher than the number of commonly available real-time macroeconomic series. All macro series were obtained with the Federal Reserve Bank of Philadelphia Real-Time Dataset for Macroeconomists. All the financial series refer to the last day of the second month of each quarter. Table 3 lists the data used, as well as the transformation applied to each series in order to ensure stationarity. In total, I use 15 macroeconomic series, 60 financial predictors and 8 different balance-sheet measures from 4 different financial intermediaries' sectors.

3 Forecasting models

I start by examining whether simple predictive regressions augmented with balance-sheet variables provide more accurate forecasts than the simple autoregressive model.

Let y_t be the annualized growth rate from t-1 to t of the variable to be forecasted, and x_{it} the $n \times 1$ predictor vector. y_{t+h} is the h-step-ahead value of the cumulative growth rate to be forecasted, $y_{t+h} = \sum_{i=0}^{h} y_{t+i}/h$. I estimate the following model for each financial intermediary's balance-sheet variable separately:

$$y_{t+h} = \alpha + \sum_{j=1}^{P} \beta_i y_{t-j} + \gamma x_{i,t} + \varepsilon_{t+h}, \qquad (1)$$

where y_t is the economic activity being forecasted; $x_{i,t}$ is the additional balance-sheet variable in question. The horizon of the forecast is defined by h. I estimate the above models for $h =$ 0, 1, 2, 3 and 4 quarters ahead. The lag order P of the autoregressive term is defined by the Bayesian information criterion (BIC).

In order to evaluate the forecasts, I initially report the root mean squared prediction error

(RMSPE), defined as

$$RMSE^h = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_{t+h} - y^*_{t+h})},$$

where $\hat{y}_{t+h}$ is the forecast, y^*_{t+h} is the variable as observed two quarters after the quarter to which the data refer, and T is the number of out-of-sample forecasts.

In order to test whether the ratios of the RMSPEs are different from unity when comparing the financial intermediaries' balance-sheet forecasts to the benchmark autoregressive (AR) model, I use the Diebold and Mariano (1995) equal predictive accuracy test. It is known that when forecasting models are nested, and hence equal in population under the null hypothesis, the Diebold-Mariano test statistic has a non-standard asymptotic distribution. Clark and McCracken (2001) and McCracken (2007) provide additional tests to compare nested models. Nevertheless, Clark and McCracken (2013) show that, in *finite samples*, the traditional Diebold-Mariano test statistic provides a good-sized test, even in the case of nested models, when the correction suggested by Harvey et al. (1997) is used. This approach to inference is also followed by Faust and Wright (2013) when forecasting inflation.

Table 4 shows the results of these initial forecasts. Mixed results are found for the various balance-sheet variables. I find evidence that balance-sheet measures associated with security broker-dealers have a significant forecasting power for some of the economic activity indicators. There is no evidence that commercial banks' balance sheets provide any information for forecasting the economic indicators examined here. The inclusion of commercial banks' and mortgage pools' balance sheets most often leads to higher RMSPE than the ones from the benchmark AR models, though this is often not significant, especially for mortgage pools. This result is consistent with previous findings by Adrian et al. (2010), who find that the informational content of balance-sheet variables for economic activity and risk premia in equity and bond markets is mainly concentrated in the highly leveraged broker-dealers financial intermediaries.

Among the different broker-dealers' balance-sheet variables (asset, leverage and equity growth), it is also noteworthy that measures of equity and leverage are significantly more

informative than total financial assets for future economic activity . By contrast, there is no evidence that measures of broker-dealers' asset growth lead to any gains in forecast accuracy.

Table 4 shows that broker-dealers' leverage growth improves upon the autoregressive benchmark by about 10% for the 4-quarter-ahead forecasts for GDP growth. For the remaining variables forecasted, these gains are in the range of 5 to 9%, but these are rarely significant. The biggest forecasting gains are for housing investment, where broker-dealers' equity leads to a significant 15% reduction in the RMSPE. These results indicate that the predictability of broker-dealers' equity and leverage for GDP growth comes mainly from their ability to predict the housing sector.

3.1 Balance sheets and other macro and financial predictors

The simple models proposed in the previous section analyze whether financial intermediaries' balance sheets provide additional information over the benchmark AR model when forecasting economic activity. Next, I examine how the information contained in these balance sheets compares to other traditional macroeconomic and financial variables commonly used as predictors of economic activity. I use factor analysis in order to summarize the information of the real-time macroeconomic and financial data set. I then analyze whether the financial intermediaries' balance sheets provide information over and above these factors.

Consider the following forecasting model:

$$y_{t+h} = \alpha + \sum_{j=1}^{P} \beta_i y_{t-j} + \sum_{i=1}^{m} \theta_i \hat{f}_{i,t} + \varepsilon_{t+h}, \tag{2}$$

where $\{\hat{f}_{i,t}\}_{i=1}^{m}$ are the first m estimated principal components of the $r \times 1$ vector of unobserved factors F_t in the following factor model:

$$X_{it} = \lambda_i F_t + \epsilon_{it}. \tag{3}$$

The macroeconomic and financial panel data are denoted by X_{it},[7] λ_i are the factor loadings and ϵ_{it} are idiosyncratic shocks. The above model is the traditional diffusion index forecasting

[7] X_{it} does not include any financial intermediaries' balance-sheet data.

framework of Stock and Watson (2002). In order to generate forecasts with diffusion indices, one needs to choose the number of factors to be included in the forecasting regression. For the sake of parsimony, I restrict myself to forecasting regressions with the first three factors $F_{1:3,t}$.

I first examine how forecasting regressions augmented with the macrofinancial factors, as in equation (2), and estimated with my real-time data set, compare with the benchmark AR model. Table 5 shows the results for this comparison. As in Bernanke and Boivin (2003) and Faust and Wright (2009), I find no gains in forecast accuracy over the benchmark AR model for the factor-augmented forecasts. As shown by these papers, the real-time nature of the data is not responsible for the factor model's poor results. The fact that my panel is relatively small compared to the data sets traditionally used for factor analysis, as well as the fact that it significantly overrepresents financial data to the detriment of other macroeconomic indicators, might explain the factor forecasts' overall poor results.

Next, I examine how the forecasts generated by the financial intermediaries' balance-sheet models as in equation (1) compare with the macrofinancial factors in equation (2). Table 6 summarizes the results. I find similar improvements over the factor forecasts as for the benchmark AR models. Nevertheless, most of these improvements are not statistically significant. A notable exception is again the housing sector, where the gains from forecasting with broker-dealers' and shadow banks' balance sheets at longer horizons are also large and significant. As in the previous subsection, I find that the forecasting power of financial intermediaries' balance sheets is concentrated in the sectors most sensitive to credit conditions, such as housing and durable goods consumption.

3.2 When do (not) financial intermediaries' balance sheets add information?

In the previous section, I showed that models augmented with broker-dealers' leverage and equity growth, as well as shadow banks' asset growth, provide significant forecasting power beyond that already contained in traditional macroeconomic and financial series for

future economic activity. Nevertheless, forecasting regressions have recently been shown to suffer from significant instabilities, as highlighted by Giacomini and Rossi (2010). Hence, one could envision a situation where forecasting models augmented with financial intermediaries' balance-sheet variables provide more forecasting power during certain times, such as in periods marked by financial volatility, than in periods characterized by financial tranquility.

3.2.1 Evidence from Giacomini and Rossi (2010) fluctuation tests

In order to capture the time variation in the relative forecasting performance of these financial intermediaries' balance sheets, I apply Giacomini and Rossi (2010) fluctuation tests for forecast comparisons in unstable environments. Rossi and Sekhposyan (2010) apply the fluctuation tests to a wide range of models for predicting U.S. GDP growth and inflation. They find that most of the predictors either completely lost or had their predictive ability strongly diminished after the mid-1970s.

The focus of Giacomini and Rossi (2010) is the local relative predictive ability of two competing forecasting models:

$$rMSFE_t = \frac{1}{m}\left(\sum_{j=t-m/2}^{t+m/2} \hat{\epsilon}_{t+h}^2 - \sum_{j=t-m/2}^{t+m/2} \hat{\eta}_{t+h}^2\right), \tag{4}$$

where $\hat{\epsilon}_t$ and $\hat{\eta}_t$ are the out-of-sample forecast errors of the first (balance sheet) and second (AR) models, respectively. I construct rolling estimates of the relative mean square forecast errors (rMSFE) using a two-sided window (m) of 20 quarters to depict the time variation in the performance of the financial intermediaries' balance-sheet models relative to that of the simple AR model.[8]

The fluctuation tests are based on the following rescaled version of the rMSFE statistic:

$$F_{t,m}^{OOS} = \hat{\sigma}^{-1} m^{-1/2}\left(\sum_{j=t-m/2}^{t+m/2} \hat{\epsilon}_{t+h}^2 - \sum_{j=t-m/2}^{t+m/2} \hat{\eta}_{t+h}^2\right), \tag{5}$$

where $\hat{\sigma}^2$ is a heteroscedasticity and autocorrelation consistent estimator of the variance σ^2.

The null hypothesis of the tests is that the forecasting performance of both models is

[8] In the appendix, I test the robustness of the results to different window sizes.

equal at each period,

$$H_0 : E(\hat{\epsilon}_t^2 - \hat{\eta}_t^2) = 0. \tag{6}$$

Giacomini and Rossi (2010) show how to approximate the distribution of the fluctuation tests by functionals of Brownian motions and provide critical values for different significance levels and window and sample sizes.

Figures 2 to 7 plot the results of the tests, as well as their 10% critical values. Each figure shows the results for tests conducted with regressions using one financial intermediary's balance-sheet variable at a time, as in equation (1). By plotting the time variation in the $F_{t,m}^{OOS}$ statistic together with the critical values, one can easily see the periods of time when the statistic crosses the critical values, signalling that the financial intermediaries' balance-sheet models outperformed, or were outperformed by, the simple AR benchmark.

It is clear from the figures that balance sheets from commercial banks and mortgage pools have no forecasting power throughout the whole forecasting sample. For many of the indicators, models including commercial banks' leverage and equity produce forecasts that are actually statistically inferior to the benchmark AR from 2005 to early 2007.

The figures also show that there is a substantial time variation in the forecasting performance of broker-dealers' equity and leverage growth for economic activity. Whereas fluctuation tests indicate that their forecasting performance was no better than the benchmark AR model in the first part of the sample, they also show a significant increase in forecasting power during the last financial crisis and following great recession.

It is also interesting to note that broker-dealers' equity and leverage growth not only have a higher forecasting power for housing investment, but that this forecasting power also arises significantly earlier than for other predicted variables. The fluctuation test signals the superiority of the broker-dealers' equity growth model over the benchmark AR as early as the first semester of 2007.

3.3 Real-time vs. revised data

In order to clarify the importance of real-time data for the balance sheet of the financial intermediaries, this section contrasts the results obtained with real-time data and the ones estimated with the revised data of balance sheets and macroeconomic aggregates, as they were observed in the last quarter of 2010.

Results are shown in Table 7. There is little difference in the RMSPE ratios estimated with fully revised data, as in Bernanke and Boivin (2003) and Faust and Wright (2009). In most cases, the financial intermediaries' balance sheet-models with revised data compare slightly worse with the benchmark AR models than in the fully real-time case. Nevertheless, the conclusion that broker-dealers' equity and leverage growth are the most informative predictors of future economic activity is robust to the use of real-time or revised data.

4 Conclusion

This paper has conducted a time-varying, out-of-sample, real-time analysis of the predictive power of various aggregate financial intermediaries' balance sheets for a range of economic activity indicators in the United States. I find that significant forecasting power is restricted to balance sheets from the more leveraged financial sector, namely broker-dealers. I also show that there are significant forecasting instabilities in the performance of balance-sheet models. Through Giacomini and Rossi (2010) fluctuation tests, I find that the positive performance of broker-dealers' balance-sheet forecasting models occurs mainly during the crisis period.

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Table 1: Composition of Balance-Sheet Variables

Financial Intermediaries	Variables
Broker-Dealers (BD)	Broker-Dealers
Commercial Banks (CB)	Commercial Banks Savings Institutions Credit Unions
Shadow Banks (SB)	Asset-Backed Securities Issuers Finance Corporations Funding Corporations
Mortgage Pools (MP)	Mortgage Pools

Note: This table shows the composition of all balance-sheet indicators used in the analysis. All data were gathered from the Federal Reserve Board Flow of Funds data. Equity is defined as total financial assets minus total financial liabilities, $(A - L)$. Leverage is defined as total financial assets over equity, $A/E = A/(A - L)$.

Table 2: Summary Statistics of Balance-Sheet Explanatory Variables

	BDA	BDL	BDE	CBA	CBL	CBE	SBA	MPA
Mean	14.86	7.91	11.26	6.58	-3.77	14.30	12.37	10.20
Median	15.29	8.61	8.68	7.29	-1.97	10.08	13.09	10.18
SD	20.93	29.02	23.35	3.54	16.04	22.90	9.18	17.87
Min	-40.65	-64.67	-37.30	-1.94	-46.74	-30.27	-21.42	-80.03
Max	97.45	100.04	94.31	14.14	46.00	107.83	37.20	45.83
AR(1)	0.75	0.72	0.71	0.91	0.73	0.74	0.99	0.99

Note: The balance-sheet sample is quarterly and goes from 1985Q1 to 2010Q4 as recorded in the 2010Q4 vintage. All data refer to annual growth rates in percentage points. BDA: Broker-Dealers Asset, BDL: Broker-Dealers Leverage, BDE: Broker-Dealers Equity, CBA: Commercial Banks Asset, CBL: Commercial Banks Leverage, CBE: Commercial Banks Equity, SBA: Shadow Banks Asset, MPA: Mortgage Pools Asset.

Table 3: Variables and Transformations in Our Large Data Set

Variable	Transf	Variable	Transf
Macroeconomic Variables (15)			
Gross Domestic Product	2	S&P 500	2
Personal Consumption Expenditures	2	Moody's Aaa yield	1
PCE Durables	2	Moody's Baa yield	1
Private Investment	2	Moody's Baa-Aaa spread	1
Housing	2	1-Month Euro Dollar rate	1
Inventories	2	3-Month Euro Dollar rate	1
Federal Government Expenditure	2	6-Month Euro Dollar rate	1
State and Local Government Expenditure	2	Exchange Rate: Switzerland	2
Exports	2	Exchange Rate: UK	2
Imports	2	Exchange Rate: Canada	2
Industrial Production	2	Oil Price	2
Capacity Utilization	2		
Non-farm Payroll	2	*Balance Sheets (8)*	
GDP Deflator	3		
M2	3	Broker-Dealers Asset Annual Growth rate	1
		Broker-Dealers Equity Annual Growth rate	1
Financial Variables (60)		Broker-Dealers Leverage Annual Growth rate	1
Fama-French Factor: RmRf	1	Commercial Banks Asset Annual Growth rate	1
Fama-French Factor: SMB	1	Commercial Banks Leverage Annual Growth rate	1
Fama-French Factor: HML	1	Commercial Banks Equity Annual Growth rate	1
Fama-French Stock Portfolios (25)	1	Shadow Banks Asset Annual Growth rate	1
Momentum Factor	1	Mortgage Pools Asset Annual Growth rate	1
Fed Funds Rate	1		
3-Month TBill rate	1		
6-Month constant maturity Treasury yield	1		
6-Month constant maturity Treasury Spread	1		
1-Year constant maturity Treasury yield	1		
1-Year constant maturity Treasury Spread	1		
2-Year constant maturity Treasury yield	1		
2-Year constant maturity Treasury Spread	1		
3-Year constant maturity Treasury yield	1		
3-Year constant maturity Treasury Spread	1		
5-Year constant maturity Treasury yield	1		
5-year constant maturity Treasury Spread	1		
7-year constant maturity Treasury yield	1		
7-Year constant maturity Treasury Spread	1		
10-Year constant maturity Treasury yield	1		
10-Year constant maturity Treasury Spread	1		
3-Month nonfinancial commercial paper Yield	1		
3-Month nonfinancial commercial paper Spread	1		
3-Month Euro Dollar Rate Spread	1		

Note: This table shows our data set, as well as the transformation applied to each one of the series: 1-No change, 2-1st difference of log, 3-2nd difference of log.

Table 4: Relative Root Mean Squared Prediction Error of Alternative Balance-Sheets Augmented Models *vs* Direct Autoregression

		BDA	BDL	BDE	CBA	CBL	CBE	SBA	MPA
GDP	h=0	1.00	0.99	0.97	1.02	1.03	1.02	0.98*	1.00
	h=1	1.00	0.99	0.96	1.03	1.05	1.02	0.98*	1.00
	h=2	1.00	0.92*	0.94	1.02	1.05	1.03	0.99	1.00
	h=3	1.00	0.90*	0.92	1.03	1.03	1.02	0.99	1.00
	h=4	1.00	0.89**	0.91	1.02	1.02	1.02	0.99	1.00
Investment	h=0	1.04*	0.99	0.99	1.00	1.02	1.01	1.02	1.01
	h=1	1.03	0.97	0.98	1.00	1.03	1.01	1.03*	1.00
	h=2	1.02	0.96	0.96	1.00	1.04	1.02	1.03	0.99
	h=3	1.01	0.93	0.95	1.00	1.03	1.02	1.03	0.99
	h=4	1.00	0.93	0.95	1.00	1.03	1.03	1.02	0.98
Housing	h=0	1.02	1.15	0.95***	1.01	1.20***	1.12***	1.00	1.00
	h=1	1.02	1.04	0.94	1.00	1.20**	1.13**	1.00	1.01
	h=2	1.01	0.93	0.91*	0.99	1.18**	1.13**	0.99	1.01
	h=3	0.99	0.91**	0.86*	0.98	1.13**	1.08*	0.99	1.01
	h=4	0.98	0.94**	0.85*	0.98	1.06*	1.02	0.98	1.01
Non-farm Payroll	h=0	1.00	0.99	0.95*	1.03	1.02	1.01	0.99*	1.00
	h=1	1.01	0.96	0.94	1.05	1.03	1.01	0.99	1.00
	h=2	1.01	0.95	0.93	1.05	1.05	1.03	0.99*	1.00
	h=3	1.01	0.95	0.93	1.05	1.04	1.03	0.99	1.00
	h=4	1.01	0.95	0.94	1.05	1.02	1.02	0.99	1.00
Durables	h=0	0.99	1.01	1.00	1.03	1.12*	1.10*	0.97	0.99
	h=1	1.03	0.98	1.01	1.04	1.15	1.12	1.00	0.99
	h=2	1.01	0.96	0.95	1.03	1.11	1.09	0.98	0.98
	h=3	0.99	1.00	0.98	1.01	1.06	1.04	1.01	0.99
	h=4	1.00	0.93**	0.95	1.01	1.04	1.03	1.00	0.99
IP	h=0	1.00	1.02	0.98	1.00	1.01	1.02	1.00	1.01
	h=1	1.02	1.01	0.96	1.01	1.02	1.01	1.00	1.01
	h=2	1.03	0.98	0.96	1.01	1.00	1.01	1.00	1.01
	h=3	1.01	0.97	0.96	1.00	1.00	1.01	1.00	1.01
	h=4	1.01	0.95	0.95	1.00	0.99	1.00	1.00	1.01

Notes: Sample: 1985Q1 to 2010Q4. Entries in the table denote the ratio of the RMSPE from each balance-sheet augmented autoregression to the RMSPE from a direct autoregression. The out-of-sample forecasts start at 1999Q2 and are fully real-time. One, two and three asterisks are assigned to entries in which the relative root mean square prediction error is significantly different from one at the 10, 5 and 1 percent significance levels, respectively. These are based on the two-sided test of Diebold and Mariano (1995), implemented as described in the text. BDA: Broker-Dealers Asset, BDE: Broker-Dealers Equity, BDL: Broker-Dealers Leverage, CBA: Commercial Banks Asset, CBE: Commercial Banks Equity, CBL: Commercial Banks Leverage, SBA: Shadow Banking Assets, MPA: Mortgage Pools Assets.

Table 5: Relative RMSPE of Real-Time Out-of-Sample Macrofinancial Factor Forecasts *vs* Benchmark Autoregressive

Economic Indicator	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$
Gross Domestic Product	1.05	1.04	1.01	0.99	0.95
Investment	1.06	1.01	1.04	1.03	1.01
Housing	1.06	1.02**	1.06*	1.03	1.06
Non-farm Payroll	1.02	0.99	1.01	1.02	1.03
Durables	1.14	1.11	1.17	1.08	1.12
Industrial Production	0.99	1.08	1.05	1.09	1.09

Note: Sample: 1985Q1 to 2010Q4. Entries in the table denote the ratio of the RMSPE from the factor-augmented autoregression to the RMSPE from a direct autoregression. The out-of-sample forecasts start at 1999Q2 and are fully real-time. Factor forecasts use the first three principal components from the macrofinancial data set. One, two and three asterisks are assigned to entries in which the relative root mean square prediction error is significantly different from one at the 10, 5 and 1 percent significance levels, respectively. These are based on the two-sided test of Diebold and Mariano (1995), implemented as described in the text.

Table 6: Relative RMSPE of Alternative Balance-Sheets' Real-Time Forecasts *vs* Macrofinancial Factor Forecasts

		BDA	BDL	BDE	CBA	CBL	CBE	SBA	MPA
GDP	h=0	0.96	0.94	0.93	0.98	0.99	0.97	0.94	0.96
	h=1	0.96	0.95	0.92	0.98	1.00	0.98	0.94	0.96
	h=2	1.00	0.91	0.93	1.02	1.04	1.02	0.98	0.99
	h=3	1.01	0.91	0.93	1.04	1.04	1.04	1.00	1.01
	h=4	1.04	0.94	0.96	1.07	1.06	1.07	1.04	1.05
Investment	h=0	0.98	0.93	0.93	0.95	0.96	0.95	0.96	0.95
	h=1	1.01	0.95	0.96	0.99	1.01	1.00	1.01	0.98
	h=2	0.98	0.92	0.92	0.96	0.99	0.98	0.98	0.95
	h=3	0.98	0.90	0.92	0.97	1.00	0.99	1.00	0.96
	h=4	0.99	0.91	0.94	0.99	1.01	1.01	1.01	0.97
Housing	h=0	0.96	1.08	0.89	0.94	1.12	1.05	0.94	0.94
	h=1	1.00*	1.02	0.92**	0.98**	1.17	1.11	0.98**	0.98**
	h=2	0.95	0.88*	0.86*	0.94	1.11	1.07	0.94*	0.95
	h=3	0.96	0.88**	0.83*	0.95	1.09	1.05	0.96	0.98
	h=4	0.93	0.89**	0.80*	0.93	1.00	0.97	0.93	0.96
Non-farm Payroll	h=0	0.98	0.97	0.93**	1.00	1.00	0.98	0.97	0.98
	h=1	1.02	0.98	0.95	1.07	1.05	1.02	1.00	1.01
	h=2	1.00	0.94	0.91	1.04	1.04	1.02	0.98	0.99
	h=3	0.99	0.93	0.92	1.03	1.02	1.01	0.98	0.99
	h=4	0.97	0.92	0.91	1.02	0.99	0.99	0.96	0.97
Durables	h=0	0.88	0.89	0.88	0.91	0.99	0.97	0.85*	0.88*
	h=1	0.93	0.89	0.91	0.94	1.04	1.01	0.90	0.89
	h=2	0.86	0.82	0.81	0.88	0.95	0.93	0.84	0.84
	h=3	0.92	0.92	0.90	0.94	0.98	0.96	0.93	0.91
	h=4	0.89	0.83**	0.84	0.90	0.92	0.92	0.89	0.88
IP	h=0	1.01	1.03	0.99	1.01	1.02	1.03	1.01	1.00
	h=1	0.95	0.94	0.90	0.93	0.95	0.94	0.93	0.99
	h=2	0.98	0.93	0.92	0.96	0.95	0.96	0.95	1.01
	h=3	0.92	0.89	0.88	0.92	0.91	0.92	0.92	1.01
	h=4	0.93	0.87	0.88	0.92	0.91	0.92	0.92	1.00

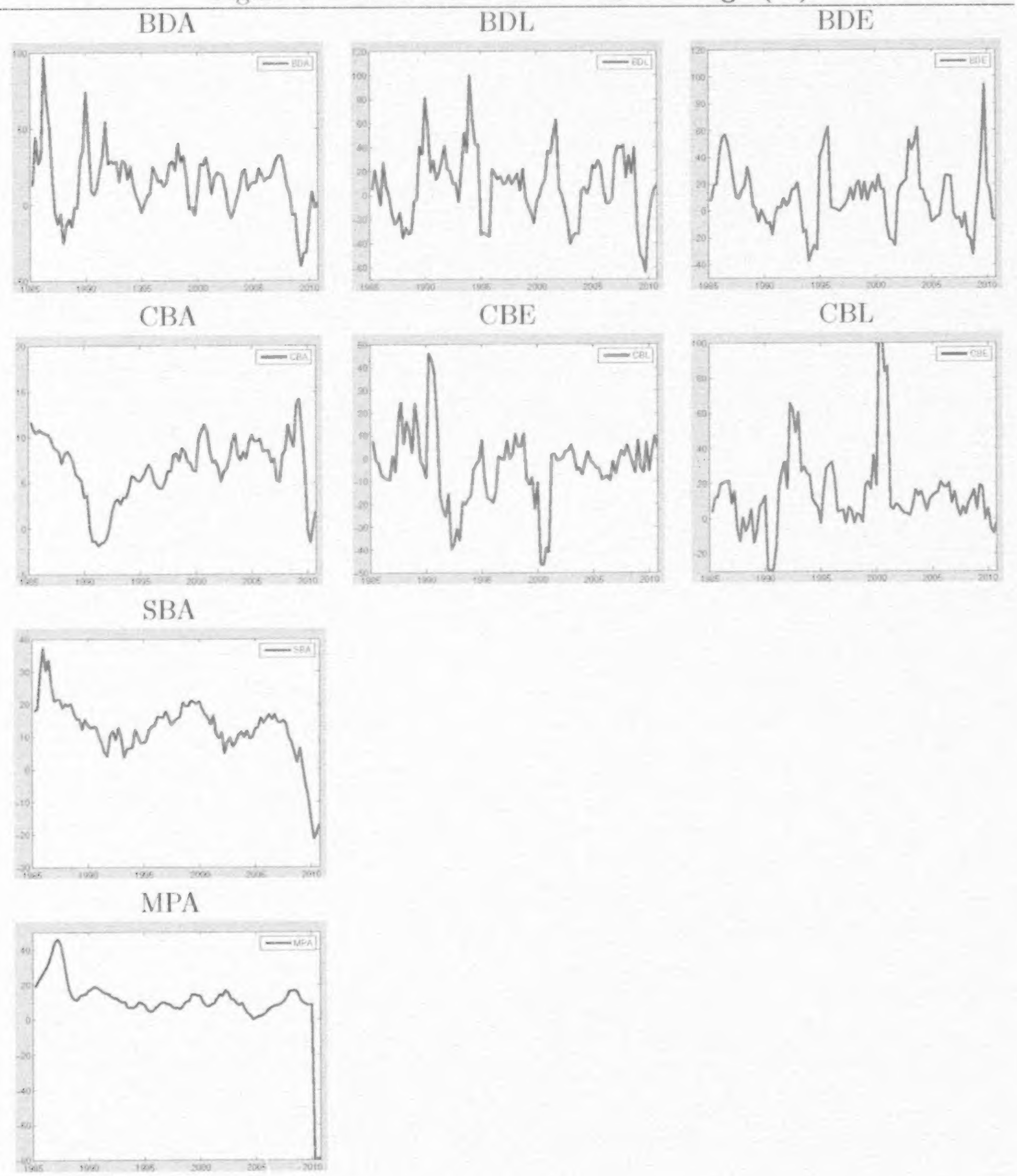
Note: Same as Table 4, except that the benchmark model is the factor-augmented autoregression as in equation (2) with $m = 3$.

Table 7: Relative Root Mean Square Error of Alternative Balance Sheets over Benchmark Autoregressive - Final Revised Data

		BDA	BDL	BDE	CBA	CBL	CBE	SBA	MPA
GDP	h=0	1.00	1.00	0.98	1.02	1.02	1.03	0.98*	1.00
	h=1	1.00	0.99	0.97	1.04	1.04	1.05	0.98	1.00
	h=2	1.01	0.97	0.94	1.05	1.05	1.06	0.98	1.00
	h=3	1.00	0.95*	0.93	1.04	1.05	1.05	0.99	1.00
	h=4	1.00	0.94*	0.93*	1.03	1.04	1.04	0.99	1.00
Investment	h=0	1.04	1.00	1.01	1.00	1.01	1.02	1.02*	1.01
	h=1	1.03	0.98***	1.00	1.00	1.02	1.03	1.03*	1.00
	h=2	1.02	0.97**	0.98	1.00	1.03	1.04	1.03*	1.00
	h=3	1.01	0.96**	0.96	0.99	1.04	1.05	1.03	1.00
	h=4	1.01	0.95**	0.95	0.99	1.05	1.06	1.03	0.98
Housing	h=0	1.03	1.00	0.98	1.00	1.14***	1.16*	1.00	1.01
	h=1	1.02	0.98	0.97	1.00	1.12*	1.14	1.00	1.01
	h=2	1.01	0.96	0.96	1.00	1.11**	1.13	0.99	1.01
	h=3	0.99	0.93*	0.95	0.99	1.10***	1.11	0.99	1.01
	h=4	0.98	0.93*	0.97	0.99	1.07***	1.08	0.98	1.01
Non-farm Payroll	h=0	1.00	1.00	0.96*	1.03	1.03	1.07	1.00	1.00
	h=1	1.01	0.98	0.94	1.05	1.07	1.11	0.99	1.00
	h=2	1.01	0.96	0.92*	1.04	1.07	1.11	0.99	1.00
	h=3	1.01	0.95	0.92*	1.04	1.08	1.11	0.99	1.00
	h=4	1.01	0.94	0.92*	1.04	1.07	1.11	0.99	1.00
Durables	h=0	0.98	1.01	0.99	1.03	1.05	1.07	0.96	1.00
	h=1	1.01	0.99	0.97	1.05	1.06	1.09	0.99	0.99
	h=2	1.00	0.98	0.96	1.03	1.06	1.09	0.97	0.99
	h=3	1.00	0.98	0.97	1.02	1.06	1.09	1.00	0.99
	h=4	1.00	0.97	0.95	1.01	1.03	1.06	1.00	1.00
IP	h=0	1.00	1.01	1.00	0.99	1.01	1.02	0.99	1.00
	h=1	1.02	1.01	0.98	1.00	1.04	1.05	1.00	1.00
	h=2	1.02	1.00	0.97	1.00	1.05	1.05	0.99	1.00
	h=3	1.01	0.99	0.98	1.00	1.05	1.05	1.00	1.00
	h=4	1.01	0.99	0.97	1.00	1.05	1.06	1.00	1.00

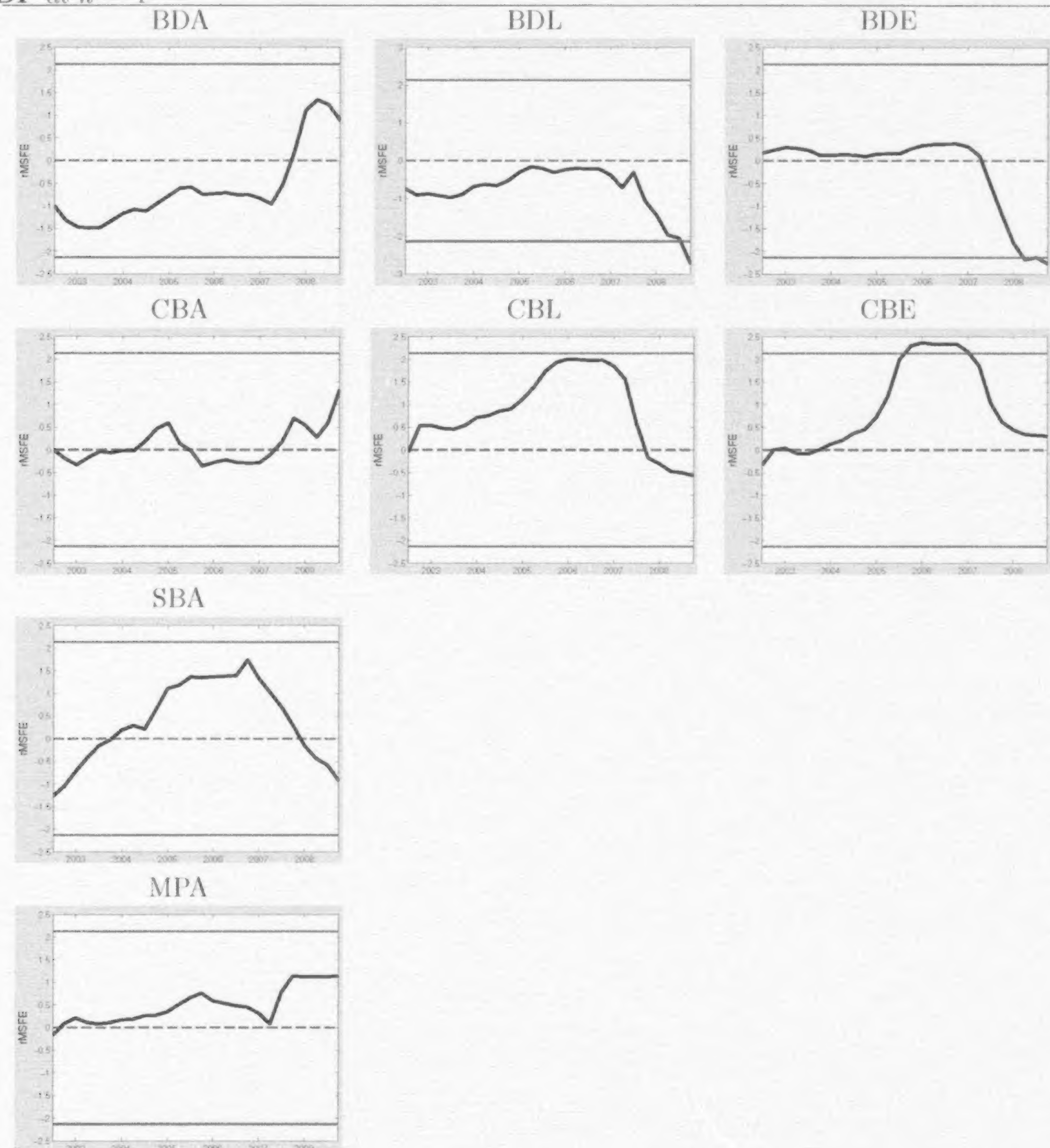
Note: Same as Table 4, except that models used final revised data as of 2010Q4.

Figure 1: **Balance Sheets Annual Change (%)**



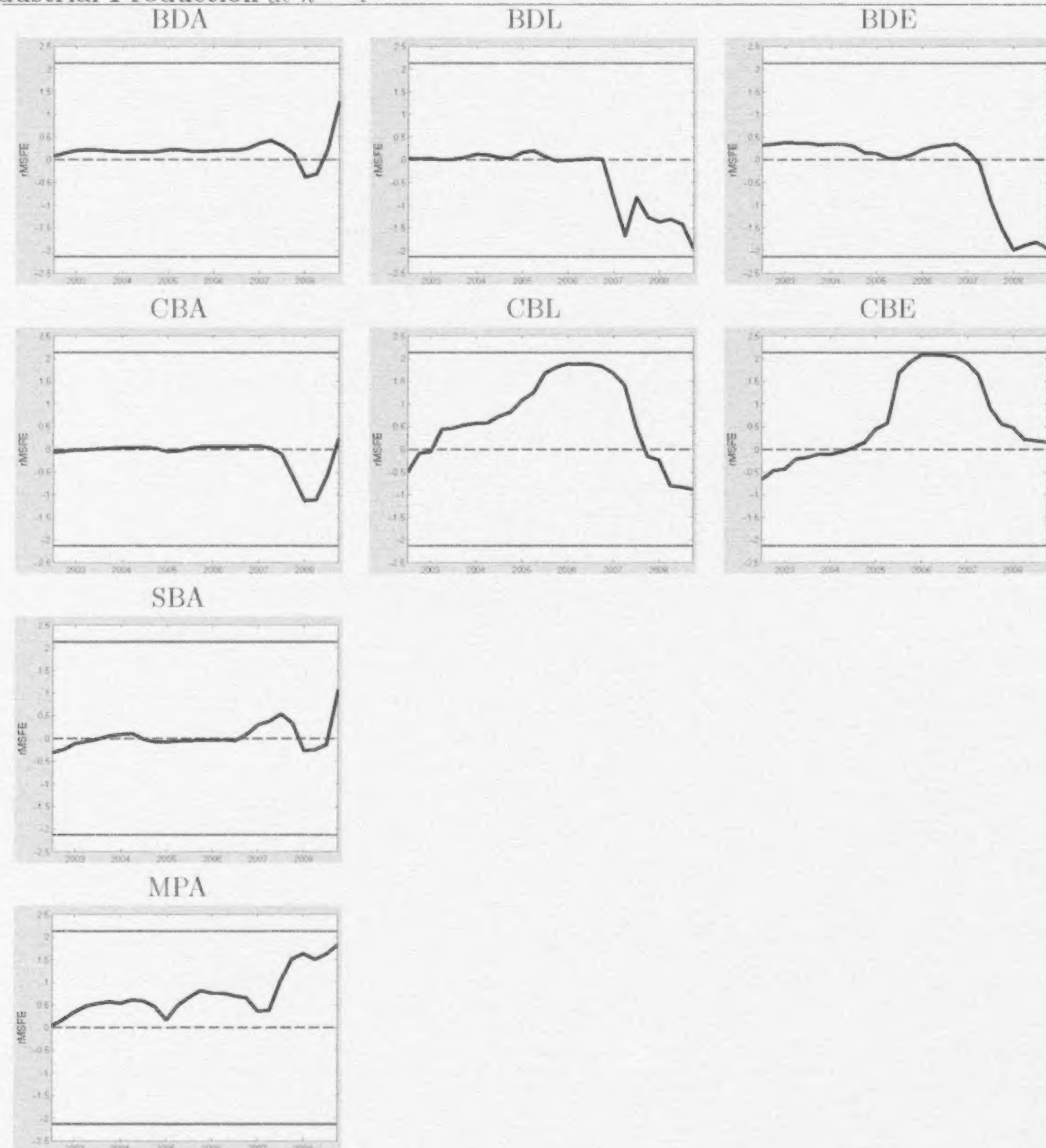
Notes: This figure shows the different balance-sheet variables from 1985Q1 to 2010Q4. All data refer to annual growth rates in percentage points, as recorded in the 2010Q4 vintage. BDA: Broker-Dealer Asset, BDL: Broker-Dealer Leverage, BDE: Broker-Dealer Equity, CBA: Commercial Banks Asset, CBL: Commercial Banks Leverage, CBE: Commercial Banks Equity, SBA: Shadow Banks Asset, MPA: Mortgage Pools Asset.

Figure 2: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability for **GDP** at $h = 4$



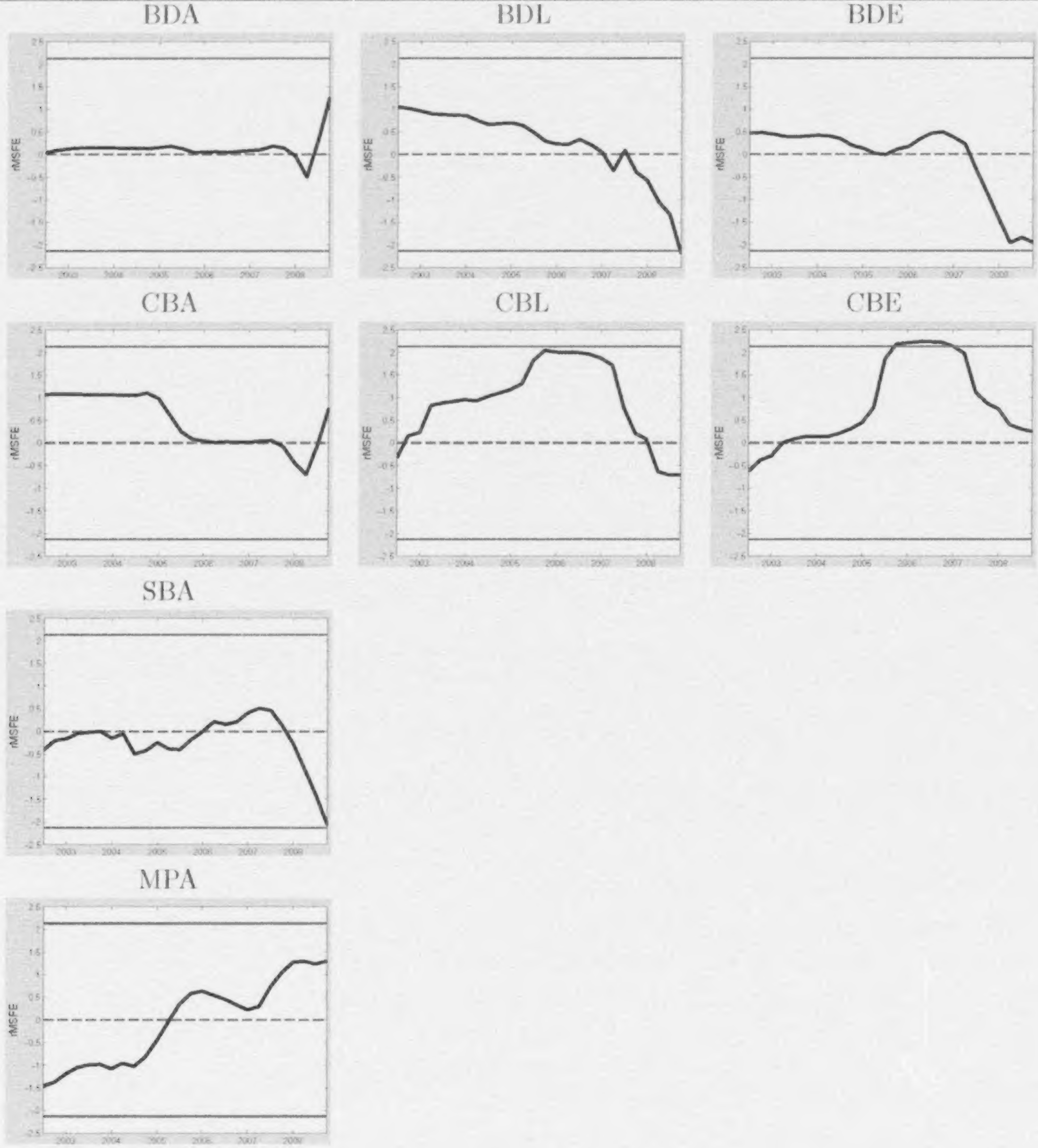
Notes: The figures show Giacomini and Rossi (2010) fluctuation test for equal out-of-sample predictability at $h = 4$, centered at time t with a two-sided window of 20 quarters for each of the balance-sheets' augmented forecasting models. Fluctuation test critical value at the 10% significance level (2.13 and -2.13) in blue; if the fluctuation test statistic exceeds the critical value, the null that the benchmark model is the true model is rejected for the particular window. Benchmark model is direct autoregression.

Figure 3: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability for **Industrial Production** at $h = 4$



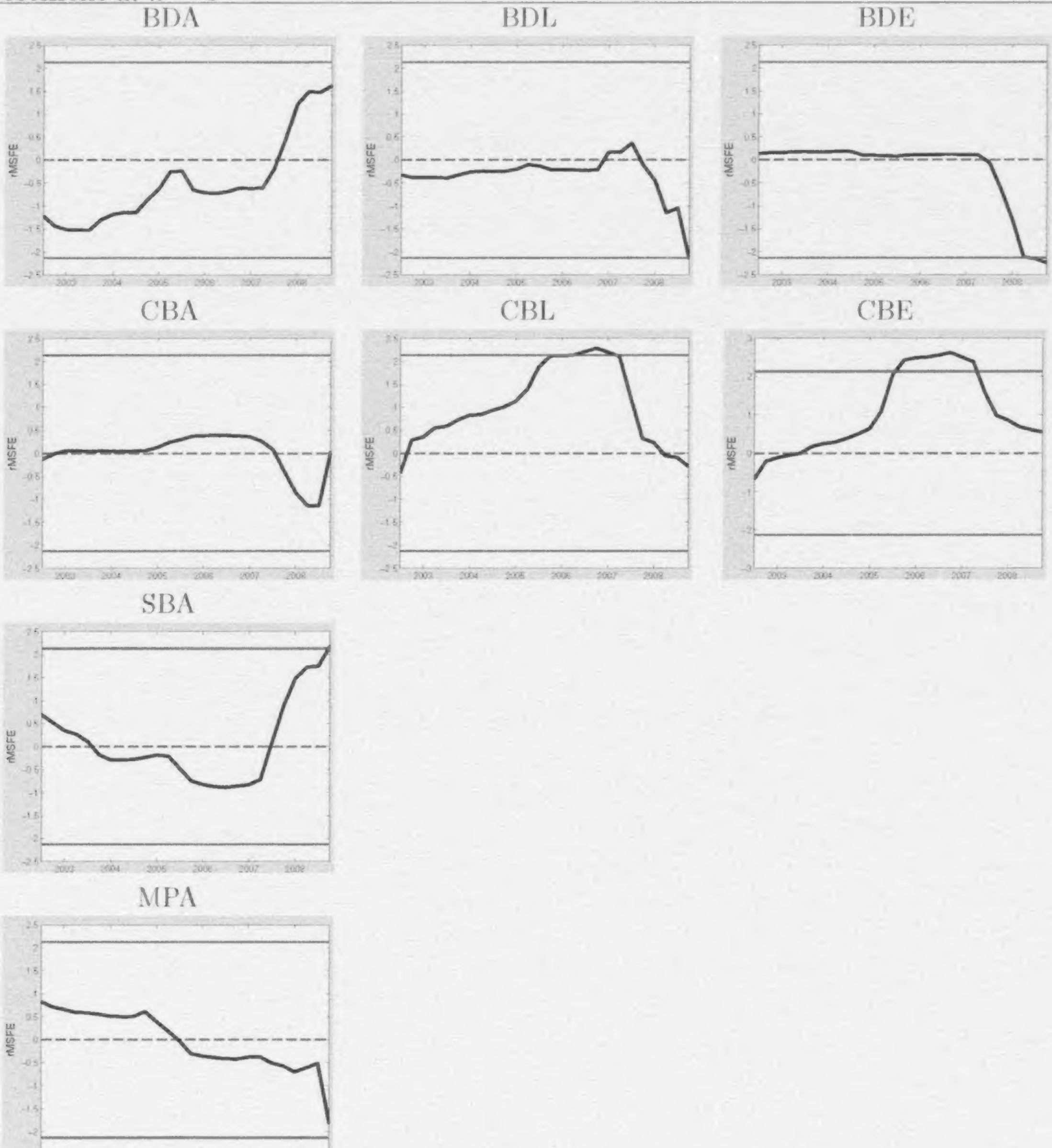
Notes: Same as Figure 2.

Figure 4: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability for **Non-farm Payroll** at $h = 4$



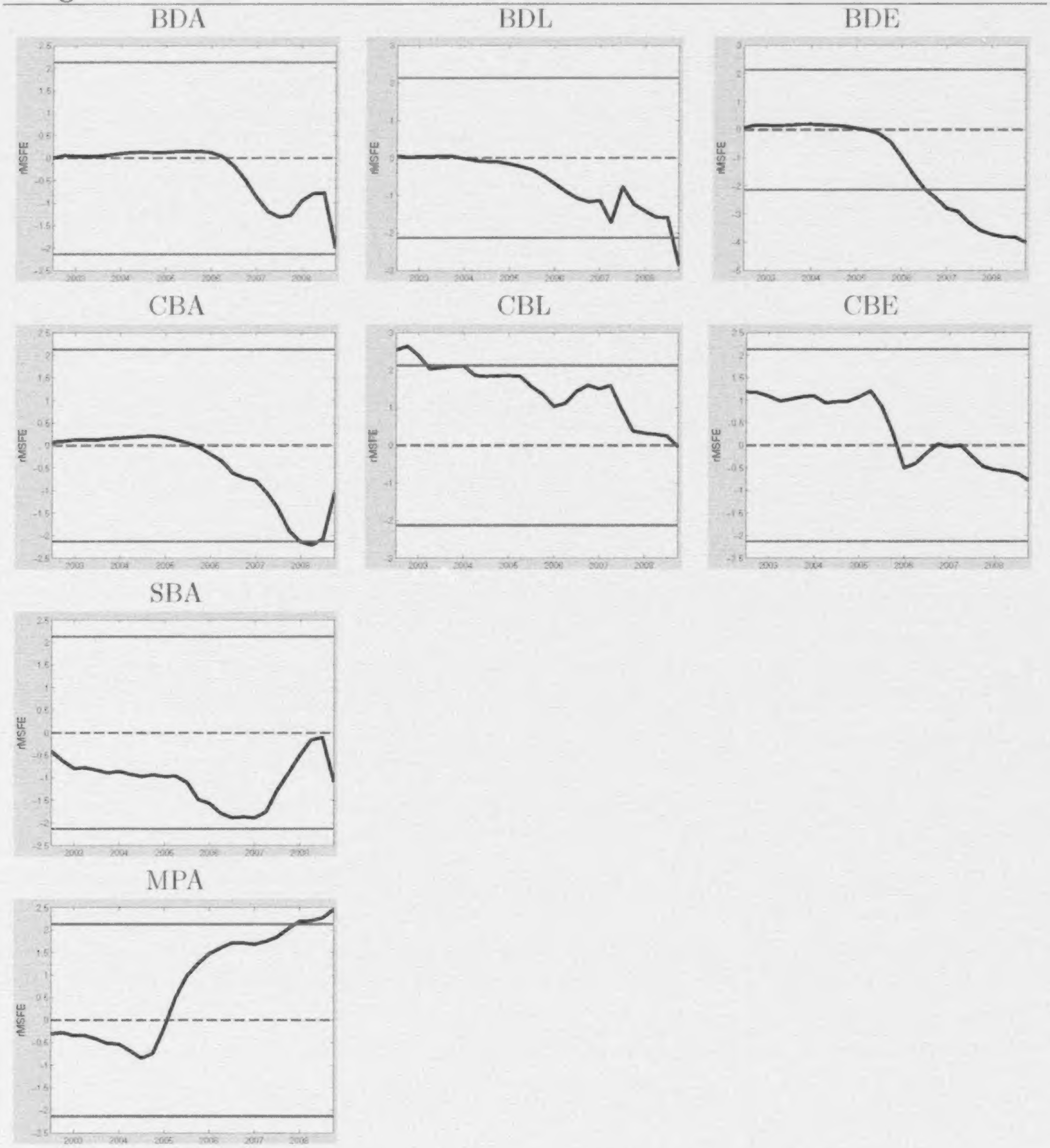
Notes: Same as Figure 2.

Figure 5: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability for **Investment** at $h = 4$



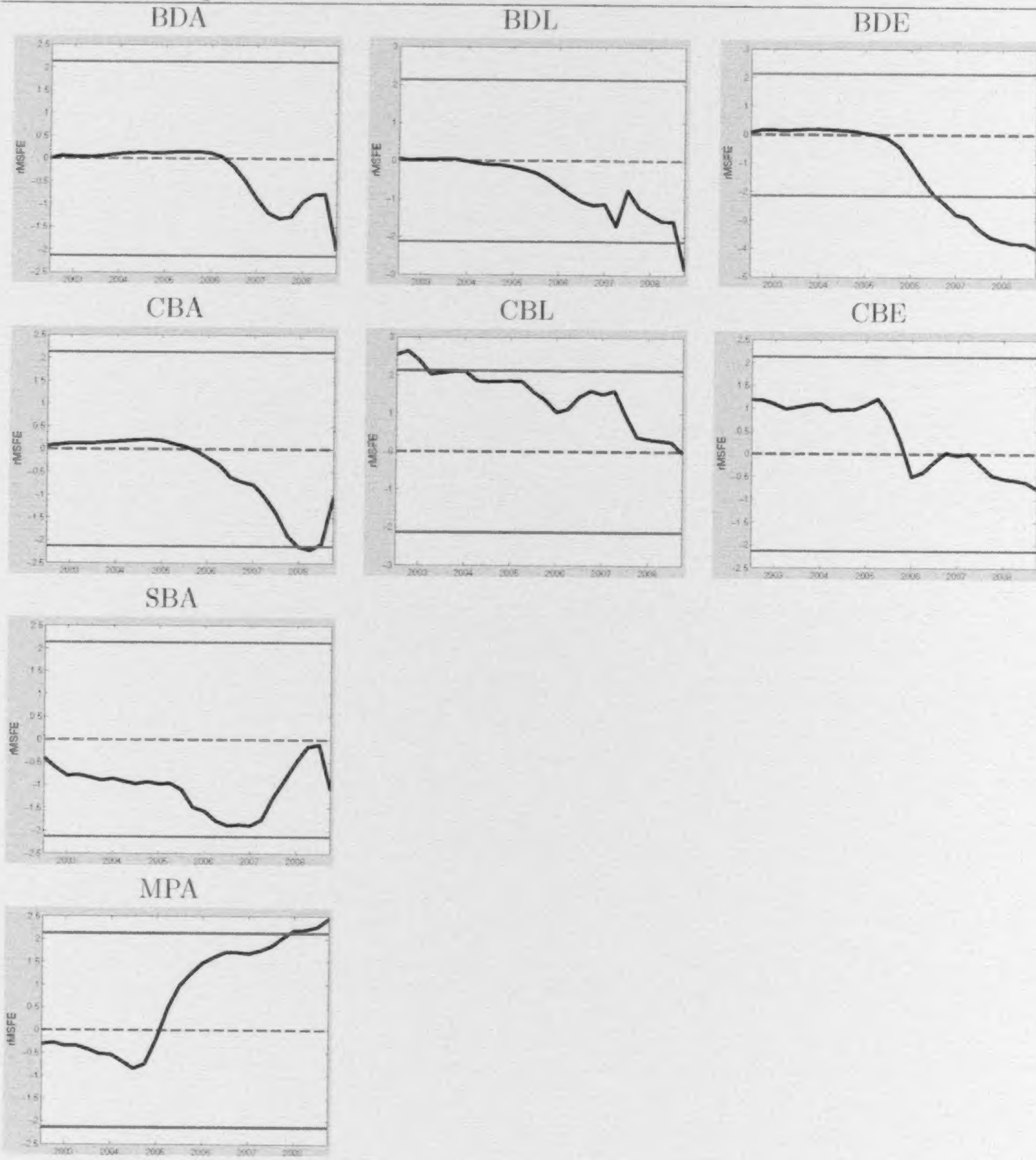
Notes: Same as Figure 2.

Figure 6: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability for **Housing** at $h = 4$



Notes: Same as Figure 2.

Figure 7: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability for **Durables Consumption** at $h = 4$



Notes: Same as Figure 2.